# Semantic description of methods for robotic deformable object manipulation

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*Abstract*— **The problem of robotic deformable object manipulation (DOM) has increased interest in the academic field. Methods involving various software and hardware components have been proposed and are bound to change. Solutions based on different approaches coexist, potentially with a strong focus on certain types of soft objects. Hence, when designing a robotic system capable of handling soft objects of different natures, this multitude of solutions is difficult to manage.**

**This paper proposes a methodological approach to this problem. We categorize methods for DOM based on a semantic description of the soft object and its manipulation context. Moreover, we propose a listing of data types relevant to DOM for specifying hardware and software components. The methodology identifies and bridges gaps in the state of the art. This contribution is a base for future developments in computer-aided design of robotic systems involving DOM.**

## I. Introduction

It is commonly admitted that manipulating deformable objects with robots requires specific contributions compared to rigid part manipulation. This specificity affects many aspects of robotics, including perception, modeling, planning, control, and actuator technology [1]. Surveys indeed highlight the variety of approaches that have been developed to address the deformable nature of soft objects [2]–[6]. They also evidence that such approaches are often aimed at objects with specific characteristics, and/or in specific manipulation contexts. For instance, operations such as cloth folding [7], [8] or cable routing [9], [10] are heavily investigated.

Contributions are based on different methodologies, which introduces incompatibilities between approaches. To name a few, we may think about:

- deformation modeling, with radically different approaches of machine learning or real-time dynamic simulation,
- shape control algorithms, where model-based and model-free methods coexist,
- perception algorithms, where visual, tactile, and force-based modalities coexist.

When designing a robotic system that manages objects of different characteristics in different contexts, the problem of finding an efficient solution in terms of hardware and software components is exacerbated. We target reconfigurable assembly cells or household robot assistants, which are supposed to perform a broad range of operations. Ideally, the number of components to be developed should remain limited, and reuse should be favored [11]. A robotic system defined by the union of all relevant literature solutions would be costly and difficult to operate, needing significant efforts in all aspects (sensor integration, modeling, programming, and so on). Hence, there is a need for a methodology that helps the designer pick a solution that performs a maximum of operations with a minimal number of components.

*Contribution:* To lay the foundations of such a methodology, we propose formalizing soft object and manipulation context properties. In particular, a semantic approach is proposed to find suited hardware and software components. Using this approach, we identify similarities and gaps wrt. the state of the art. While the design approach is not automated and requires extensive bibliography knowledge, limiting its potential, we believe that this early work can spark interest among the community, identify scientific gaps formally, and help direct future efforts.

## II. Semantic description of methods

*Knowledge modeling:* The proposed methodology needs to use the knowledge in the field of DOM, to pick hardware and implement programs. Hence, we are faced with the need to capture this knowledge. In systems engineering, a common approach involves using modeling languages [12]. Generic models for robotic system description have been proposed, such as the Core Ontology for Robotics and Automation from IEEE 1872-2015 standard [13]. However, they do not consider concepts linked with DOM, limiting their use in this context. In line with definitions of ontology modeling, as presented in their application to robotics in [14], we propose:

- a list of properties to identify different types of deformable objects (ontological classes),
- those properties having a finite set of semantic (ie. non-numeric) values (ontological functions).

*Property listing:* We build upon the bibliography to propose the list of deformable object properties and their associated semantic values.

| |
|---|
| Property: GraspingModality<br>Values: {*pinch, suction, magnetic, ...*} |

This property explores the physical effect used for grasping. It is directly linked with actuator technology. Pinch grasping through parallel grippers is encountered in many applications [10], [15]. However, grasping an object by both sides may prevent establishing contact with the environment, such as in layering operations [16], [17]. Knowledge of

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context and object properties allows for choosing suitable grasping modalities.

Property: OBJECTGEOMETRY
Values: {*uniparam, biparam, triparam*}

This property relates to the object's geometry and in particular, the existence of symmetries and negligible dimensions. Uniparametric objects are cables or belts, biparametric objects are clothes or shells. The influence of object geometry on solutions for manipulation has been identified clearly in surveys [2], [3], [6].

Property: OBJECTBEHAVIOR
Values: {*isometric, extensible, flexrigid, foldable, elastic, plastic*}

This property relates to the deformation characteristics of the object. We propose a classification along three criteria (i) tensile behavior along non-negligible dimensions (ii) flexion behavior along non-negligible dimensions (iii) reversibility of deformation. Respectively, an object may encounter isometric deformation or stretch, oppose resistance to flexion or not, and deform elastically or plastically.

Combining OBJECTGEOMETRY with OBJECTBEHAVIOR, it is easy to identify commonly encountered types of objects. Some examples are proposed in the following list.

- Towel: *biparametric isometric foldable elastic*
- Origami: *biparametric isometric foldable plastic*
- Rubber seal: *biparametric extensible flexrigid elastic*
- Wire harness: *uniparametric isometric flexrigid elastic*

Property: CONTACTBEHAVIOR
Values: {*avoid, sliding, sticky*}

This property relates to the context of the operation and the possibility to undergo environmental contact. We distinguish here three cases. The first case consists in avoiding other contacts than at the grasping points, which is typical for transportation [18]. The second case consists in having sliding contacts, thus allowing the usage of an external surface to maintain the object in a given position (eg. a table for cloth folding). Finally, objects that are sticky or impregnated with glue have an adhesive behavior, which notably makes precise positioning more tedious than in the sliding case.

Property: TARGETQUANTITY
Values: {*point, pcl, contour, parametricshape, planarity, tension, strain, stress, hardness*}

This property relates to the quantities of interest for the successful completion of manipulation in a given context. We consider here not only the main goal but also variables that are constraints in the problem. For instance, a shape control algorithm may aim at reaching a desired state represented by a pointcloud, while enforcing limits on stresses within the object to avoid damaging it. Semantic values such as the coordinate of a (cloud of) point(s) are common targets for DOM control algorithms [19], [20]. Foldline positioning may be thought as a specific case of pointcloud-based target definition [21]. Contour-based target definition was also explored [22]. Parameter-based definitions of shapes may be used for some uniparametric or biparametric objects [16], [23]. Planarity measures are of interest for wrinkle removal [24]. Tension control in belt-like objects was tackled in [23]. Strain and stresses may be monitored through real-time simulation. Hardness is considered when processing organic materials [25]. This list is in line with our analysis of the state of the art but is likely to evolve in the future as new contexts are tackled.

Property: PERCEPTIONQUANTITY
Values: {*pcl, partialpcl, pixelvalues, pixelcontour, pattern, wrench, contactpressure, contactdirection*}

This property relates to the raw quantities outputted by sensors in DOM context. Deformation sensing is vastly used in the field. The main reason is that loop closure brought by sensing mitigates the necessity for very fine modeling of deformation dynamics. Surveys agree upon three main modalities that are vision, force sensing, and tactile sensing. Vision-based algorithms may make use of 2D image characteristics (eg. contours [22], pattern [15] or pixel values to detect wrinkles), but depth information is also largely used [26]. It makes sense to distinguish contexts in which occlusions may occur, as special efforts are needed when object view is only partial. Wrench sensing at the robot wrist has been used to estimate deformation [27]. In-hand tactile sensors are also used to measure the magnitude of contact pressure, with more advanced sensors also capable of giving its direction [28]. In the context of multi-modal perception, many such deformation cues may be used within the same program.

Property: MODELTYPE
Values: {*explicit, implicit, discrete, surrogate, particle, constitutive, paramgiven, paramlearned, paramestimated, online, offline*}

This property relates to the nature of models used to represent object deformation. We are inclined to adopt the categorization from [4]. Firstly, the shape may be represented implicitly, explicitly, or discretely. We can think of catenary models [16] or mathematical representations [29]. Secondly, deformation dynamics may come from surrogate models (eg. learning [30]), particle systems (eg. position-based dynamics [31]), or constitutive equations (eg. finite element [19], [20], [27], [32], mass-spring models [33]). Thirdly, the parameters of such models may be given by the user (eg. following tensile testing), learned, or estimated online. Moreover, it is relevant to state whether a model can be executed in real-time or not.

## III. USAGE FOR ROBOTIC SYSTEM DESIGN

The methodology deployment is illustrated using the contribution of [23]. It consists in positioning the tip of a raw rubber band wound to a bobbin while ensuring minimal tension within the material. This is one of several operations to be performed within the flexible robotic cell, alongside cutting and assembling the rubber bands.

GRASPINGMODALITY *suction*
OBJECTGEOMETRY *uniparam*
OBJECTBEHAVIOR *isometric flexrigid elastic*
CONTACTBEHAVIOR *sticky*
TARGETQUANTITY *point tension*
PERCEPTIONQUANTITY *partialpcl pixelvalues pixelcontour*
MODELTYPE *online*

Fig. 1: Values of semantic properties for the use case.

| value | [16] | [20] | [30] | [34] | [35] |
|---|---|---|---|---|---|
| *suction* | ✓ | × | × | × | × |
| *uniparam* | ✓ | × | ✓ | ✓ | × |
| *isometric* | ✓ | × | × | ✓ | ✓ |
| *flexrigid* | ✓ | ✓ | ✓ | ✓ | ✓ |
| *elastic* | ✓ | ✓ | ✓ | ✓ | ✓ |
| *sticky* | ✓ | × | × | × | × |
| *point* | ✓ | × | × | ✓ | × |
| *tension* | ✓ | × | × | × | × |
| *partialpcl* | × | ✓ | × | × | × |
| *pixelvalues* | × | × | × | × | × |
| *pixelcontour* | × | × | × | × | × |
| *online* | ✓ | ✓ | ✓ | ✓ | ✓ |
| $D$ | 3 | 8 | 8 | 6 | 8 |

TABLE I: Abidance of methods from the literature with desired values of properties.

*Step 1 - semantic description of object and context:* This first step involves identifying semantic values for properties describing the desired operation context. At this step, we mainly revoke inappropriate solutions. The main constraints regarding our operational context are as follows: (i) the material is not magnetic and cannot be grasped by parallel fingers, since it is sticky and needs to be laid flat (ii) we wish to reuse the RGB-D camera system implemented for other operations instead of adding new sensors (iii) the object is of solid color and shows no distinguishable texture (iv) the algorithm must react to disturbances, hence we aim at controlling robot motions on-line. Taking those constraints into account, the set of ontological properties to be met is reported on Fig. 1

*Step 2 - evaluation of similarity with existing methods:* The second step consists in comparing targeted properties with methods from the literature. We check abidance with the set of properties specified above. This is illustrated in Table I, resulting in a measure of dissimilarity $D$ between methods, computed as the number of mismatched values of properties. To obtain this result, bibliography entries need to be reviewed. Identifying property values from articles requires a moderate knowledge of the field: an in-depth understanding of deployed methods is unnecessary, but use cases must be analyzed thoroughly. In deploying the methodology illustrated in Table I, one solution amongst the reviewed approaches edges ahead in terms of similarity.

*Step 3 - identification of components to be created:* In this final phase, we identify the scientific gaps to bridge wrt. the most similar solution. The main assumption here is that the lower the dissimilarity, the more relevant to the use case the methods for perception, modeling, control, etc. From Table I, properties related to object characteristics are satisfied, while mismatches are related to perception. Indeed, it appears that [16] uses the catenary model, whose assumptions are also valid in our use case of rubber band manipulation. Moreover, the catenary model provides explicit tension computation from the position of the tips. Hence, it is more suitable than finite element modeling or Kirchoff rod theory for instance. On the contrary, special efforts were needed to estimate and control tension from RGB-D measurement rather than force sensing, leading to a new contribution [23].

*Outcomes and expected gains:* The newly developed solution benefited from inferior material costs by not requiring dedicated force sensing and easier implementation by not requiring force control of robots. It was proven to control the tension adequately in quasi-static operation mode. Hence, this use case exemplifies the idea that formal analysis of literature and similarity assessment can help direct and plan scientific efforts. The result is a robotic system dedicated to DOM whose capabilities are improved with minimal material cost and low added complexity.

*Future developments:* The first challenge lies in the construction of a database of methods. To create comparisons such as in Table I, two elements are mandatory: the expertise to assign semantic values from literature analysis and the structuration of such data through software. Hence the method calls for an in-depth survey of the literature on one side, and the storage of survey results in a database on another. The second challenge consists of software assistance to explore the design space and identify methods that are optimal in terms of similarity. Early results using PDDL to manipulate semantic values showed the chaining of heterogenous components to construct a functioning robotic system. However, the required expertise to set up the PDDL problem and analyze solver outputs must be reduced for transfer to the industry.

## IV. CONCLUSION

In order to facilitate robotic system design and bibliography analysis, we propose a semantic description of methods dedicated to deformable object manipulation. It revolves around a set of properties related to soft object characteristics and manipulation context. By analyzing values of properties, the similarity between methods is evaluated. This measure can be used as assistance to the design of new algorithms which augment the capabilities of a robotic system.

A direct perspective consists of a deeper bibliographic analysis to validate and augment the number of properties and semantic values, in order to catch the specificities of each application involving deformable objects. In the long run, software tools should be proposed to facilitate methodology usage and achieve the computer-aided design of multi-purpose robotic systems dedicated to DOM.

# REFERENCES


[1] J. Zhu, A. Cherubini, C. Dune, D. Navarro-Alarcon, F. Alambeigi, D. Berenson, F. Ficuciello, K. Harada, J. Kober, X. Li, J. Pan, W. Yuan, and M. Gienger, "Challenges and Outlook in Robotic Manipulation of Deformable Objects," *IEEE Robotics and Automation Magazine*, vol. 29, no. 3, pp. 67–77, 2022. arXiv:2105.01767 [cs].

[2] P. Jiménez, "Survey on model-based manipulation planning of deformable objects," *Robotics and Computer-Integrated Manufacturing*, vol. 28, pp. 154–163, Apr. 2012.

[3] J. Sanchez, J.-A. Corrales, B.-C. Bouzgarrou, and Y. Mezouar, "Robotic manipulation and sensing of deformable objects in domestic and industrial applications: a survey," *The International Journal of Robotics Research*, vol. 37, pp. 688–716, June 2018.

[4] V. E. Arriola-Rios, P. Guler, F. Ficuciello, D. Kragic, B. Siciliano, and J. L. Wyatt, "Modeling of Deformable Objects for Robotic Manipulation: A Tutorial and Review," *Frontiers in Robotics and AI*, vol. 7, p. 82, Sept. 2020.

[5] F. Nadon, A. Valencia, and P. Payeur, "Multi-Modal Sensing and Robotic Manipulation of Non-Rigid Objects: A Survey," *Robotics*, vol. 7, p. 74, Nov. 2018.

[6] R. Herguedas, G. Lopez-Nicolas, R. Aragues, and C. Sagues, "Survey on multi-robot manipulation of deformable objects," in *2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, (Zaragoza, Spain), pp. 977–984, IEEE, Sept. 2019.

[7] J. Borras, G. Alenya, and C. Torras, "A Grasping-Centered Analysis for Cloth Manipulation," *IEEE Transactions on Robotics*, vol. 36, pp. 924–936, June 2020.

[8] Y. Avigal, L. Berscheid, T. Asfour, T. Kroger, and K. Goldberg, "SpeedFolding: Learning Efficient Bimanual Folding of Garments," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Kyoto, Japan), pp. 1–8, IEEE, Oct. 2022.

[9] A. J. Shah and J. A. Shah, "Towards manipulation planning for multiple interlinked deformable linear objects," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, (Stockholm, Sweden), pp. 3908–3915, IEEE, May 2016.

[10] S. Huo, A. Duan, C. Li, P. Zhou, W. Ma, H. Wang, and D. Navarro-Alarcon, "Keypoint-Based Planar Bimanual Shaping of Deformable Linear Objects Under Environmental Constraints With Hierarchical Action Framework," *IEEE Robotics and Automation Letters*, vol. 7, pp. 5222–5229, Apr. 2022.

[11] D. Brugali and P. Scandurra, "Component-based robotic engineering (Part I) [Tutorial]," *IEEE Robotics & Automation Magazine*, vol. 16, pp. 84–96, Dec. 2009.

[12] J. Whittle, J. Hutchinson, and M. Rouncefield, "The State of Practice in Model-Driven Engineering," *IEEE Software*, vol. 31, pp. 79–85, May 2014.

[13] "IEEE Standard Ontologies for Robotics and Automation," Tech. Rep. IEEE Std 1872-2015, 2015.

[14] A. Olivares-Alarcos, D. Beßler, A. Khamis, P. Goncalves, M. K. Habib, J. Bermejo-Alonso, M. Barreto, M. Diab, J. Rosell, J. Quintas, J. Olszewska, H. Nakawala, E. Pignaton, A. Gyrard, S. Borgo, G. Alenyà, M. Beetz, and H. Li, "A review and comparison of ontology-based approaches to robot autonomy," *The Knowledge Engineering Review*, vol. 34, p. e29, 2019.

[15] M. Aranda, J. Antonio Corrales Ramon, Y. Mezouar, A. Bartoli, and E. Ozgur, "Monocular Visual Shape Tracking and Servoing for Isometrically Deforming Objects," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Las Vegas, NV, USA), pp. 7542–7549, IEEE, Oct. 2020.

[16] S. Flixeder, T. Glück, and A. Kugi, "Force-based cooperative handling and lay-up of deformable materials: Mechatronic design, modeling, and control of a demonstrator," *Mechatronics*, vol. 47, pp. 246–261, Nov. 2017.

[17] R. K. Malhan, A. V. Shembekar, A. M. Kabir, P. M. Bhatt, B. Shah, S. Zanio, S. Nutt, and S. K. Gupta, "Automated planning for robotic layup of composite prepreg," *Robotics and Computer-Integrated Manufacturing*, vol. 67, p. 102020, Feb. 2021.

[18] D. McConachie, A. Dobson, M. Ruan, and D. Berenson, "Manipulating Deformable Objects by Interleaving Prediction, Planning, and Control," *The International Journal of Robotics Research*, vol. 39, pp. 957–982, July 2020. arXiv:2001.09950 [cs].

[19] F. Ficuciello, A. Migliozzi, E. Coevoet, A. Petit, and C. Duriez, "FEM-Based Deformation Control for Dexterous Manipulation of 3D Soft Objects," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Madrid), pp. 4007–4013, IEEE, Oct. 2018.

[20] A. Koessler, N. R. Filella, B. Bouzgarrou, L. Lequievre, and J.-A. C. Ramon, "An efficient approach to closed-loop shape control of deformable objects using finite element models," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, (Xi'an, China), pp. 1637–1643, IEEE, May 2021.

[21] I. Garcia-Camacho, M. Lippi, M. C. Welle, H. Yin, R. Antonova, A. Varava, J. Borras, C. Torras, A. Marino, G. Alenya, and D. Kragic, "Benchmarking Bimanual Cloth Manipulation," *IEEE Robotics and Automation Letters*, vol. 5, pp. 1111–1118, Apr. 2020.

[22] J. Zhu, D. Navarro-Alarcon, R. Passama, and A. Cherubini, "Vision-based manipulation of deformable and rigid objects using subspace projections of 2D contours," *Robotics and Autonomous Systems*, vol. 142, p. 103798, Aug. 2021.

[23] N. Roca Filella, A. Koessler, C. Bouzgarrou, and J. A. C. Ramon, "3D Visual-Based Tension Control in Strip-Like Deformable Objects Using a Catenary Model," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Kyoto, Japan), p. 8, Oct. 2022.

[24] C.-Y. Tsai, "Wrinkle contraction direction: a useful feature for learning robotic fabric manipulation from demonstration," Master's thesis, TU Delft, Netherlands, 2021.

[25] Z. Zhang, J. Zhou, Z. Yan, K. Wang, J. Mao, and Z. Jiang, "Hardness recognition of fruits and vegetables based on tactile array information of manipulator," *Computers and Electronics in Agriculture*, vol. 181, p. 105959, Feb. 2021.

[26] A. Petit, F. Ficuciello, G. A. Fontanelli, L. Villani, and B. Siciliano, "Using Physical Modeling and RGB-D Registration for Contact Force Sensing on Deformable Objects:," in *Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics*, (Madrid, Spain), pp. 24–33, SCITEPRESS - Science and Technology Publications, 2017.

[27] J. Sanchez, K. Mohy El Dine, J. A. Corrales, B.-C. Bouzgarrou, and Y. Mezouar, "Blind Manipulation of Deformable Objects Based on Force Sensing and Finite Element Modeling," *Frontiers in Robotics and AI*, vol. 7, p. 73, June 2020.

[28] W. Yuan, C. Zhu, A. Owens, M. A. Srinivasan, and E. H. Adelson, "Shape-independent Hardness Estimation Using Deep Learning and a GelSight Tactile Sensor," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 951–958, May 2017. arXiv:1704.03955 [cs].

[29] D. Navarro-Alarcon and Y.-H. Liu, "Fourier-Based Shape Servoing: A New Feedback Method to Actively Deform Soft Objects into Desired 2-D Image Contours," *IEEE Transactions on Robotics*, vol. 34, pp. 272–279, Feb. 2018.

[30] R. Laezza and Y. Karayiannidis, "Learning Shape Control of Elastoplastic Deformable Linear Objects," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4438–4444, May 2021. arXiv:2208.02067 [cs, eess].

[31] P. Guler, A. Pieropan, M. Ishikawa, and D. Kragic, "Estimating deformability of objects using meshless shape matching," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Vancouver, BC), pp. 5941–5948, IEEE, Sept. 2017.

[32] S. Duenser, J. M. Bern, R. Poranne, and S. Coros, "Interactive Robotic Manipulation of Elastic Objects," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (Madrid), pp. 3476–3481, IEEE, Oct. 2018.

[33] J. Das and N. Sarkar, "Autonomous Shape Control of a Deformable Object by Multiple Manipulators," *Journal of Intelligent & Robotic Systems*, vol. 62, pp. 3–27, Apr. 2011.

[34] O. Aghajanzadeh, M. Aranda, J. A. Corrales Ramon, C. Cariou, R. Lenain, and Y. Mezouar, "Adaptive Deformation Control for Elastic Linear Objects," *Frontiers in Robotics and AI*, vol. 9, p. 868459, Apr. 2022.

[35] M. Shetab-Bushehri, M. Aranda, Y. Mezouar, and E. Ozgur, "Lattice-based shape tracking and servoing of elastic objects," Sept. 2022. arXiv:2209.01832 [cs].